Mid-Term_Project_What's_Cooking

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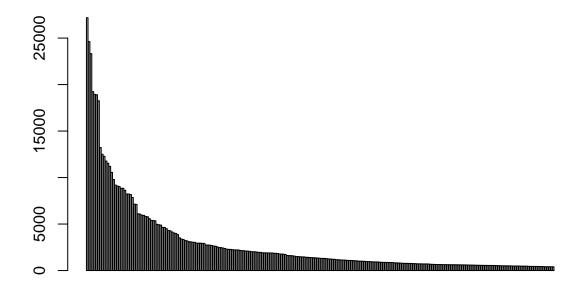
For my midterm project I analyzed data from Kaggle's data competition "What's Cooking?" containing recipes, their ingredients, and their cuisines. First thing's first, I downloaded the training data set, transformed it into a document term matrix, and did some data pre-processing with the tm package. I removed the punctuation, ensured that all of the ingredients were lowercase, removed common English words, stemmed all of the words, and removed sparse terms.

```
# textual preprocessing
ingredients <- Corpus(VectorSource(train$ingredients))
ingredients <- tm_map(ingredients, removePunctuation)
ingredients <- tm_map(ingredients, content_transformer(tolower))
ingredients <- tm_map(ingredients, removeWords, stopwords("english"))
ingredients <- tm_map(ingredients, stemDocument)

dtm <- DocumentTermMatrix(ingredients)
sparsedtm <- removeSparseTerms(dtm, 0.99)
ingredientsDTM <- as.data.frame(as.matrix(sparsedtm))</pre>
```

Then I wanted to examine the frequency and distribution of the different ingredients across the data set both with a bar plot and a word cloud of the ingredient frequencies. I also looked at the recipe distribution by cuisine.

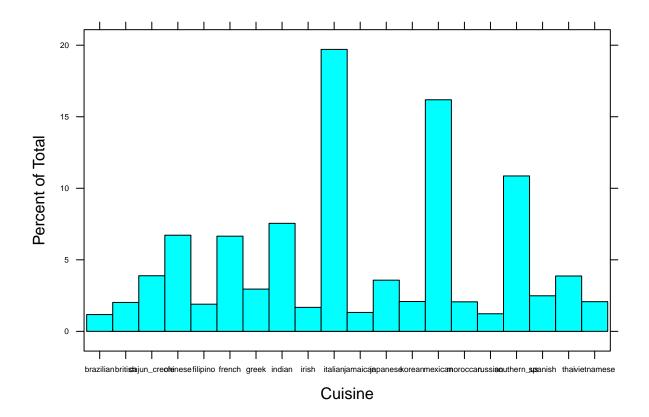
```
# Barplot
ingredientFreq <- sort(colSums(ingredientsDTM), decreasing = TRUE)
ingredientNames <- names(ingredientFreq)
barplot(ingredientFreq, cex.names = 0.5)</pre>
```



pepper red juic corn grate shred cayenn hot sweet mint yolk plum free yeast taco pecan lean greek dress

```
buttermilk lettuc shallot halv slice starch masala kernel reduc orang extravirgin oregano stock ricotta samondextract grate emon smoke boneless smoke boneless colori and starch masala kernel stock ricotta fillet toast paprika lowfat fillet toast paprika lowfat unsalt whole yogurt
                      shiitak
                                                                                                                                                                                                                                 unsalt whole yogurt chive chileflakebacon
steak g
syrupgranul b
crumb
jalapeno
                                                                       breast
                                                                                                                                                                                                                                                                             bake peel wheat aco koshercabbag soda
crumb
jalapeno
                       season
                                                                                                                                                                                                                                            drimilk bean soo
  <sub>curri</sub> brown
    frozen corn bay rec
                                                                                                                                                                                                                                                                                                              past meat
 dark
  yolk
    jack
                                                                                                                                                                                                                                                                                                            cook sea
    potato sodium light > COO
  light ≥ fine O
                                                                                                                                                                                                                                                                                                                 get in graph of the state of th
 cider COVE
  italian shred rosemari fat tortilla
                                      ਲ
 appl so lime flou thigh Elime flou
                                                                                                                   beet
                                                              <u>⊂</u>chili
                                                                                                                                                                                                                                                                                                parsley tumer
                     thyme
                                                                                                                                                                                                                                                                                 0
   coars sweet
                                                                                                                                                                                                                                                                                                coconut
                                                                                                                                                                                                                                                                                                  spray nutmeg
            peanut
                                                                                                                                                                                                                                                                                        crushcanola
                                                                                                                                                         stick
      medium sausag allpurpos, hot cilantro vinegarbread plum
                                                                                                    cream
                                                                                              ayenn broth bell sesam shrimp pasta chines roast half parmesan mushroom heavi cucumb honey mustard spinach avocado
                                 fennel
                                                          garam cayenn
                                             mayonais
```

```
# Add the dependent variable to the data.frame
ingredientsDTM$cuisine <- as.factor(train$cuisine)
histogram(ingredientsDTM$cuisine, scales = list(cex = 0.5), xlab = "Cuisine")</pre>
```

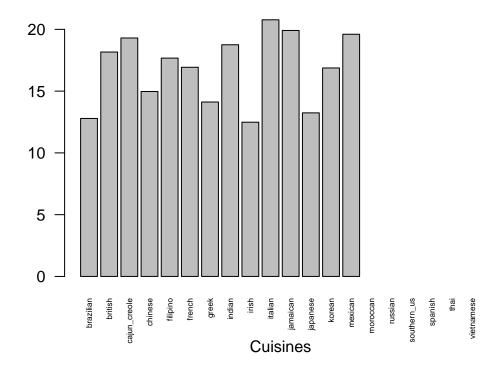


After seeing how the different ingredients were distributed, I decided to look more at cuisine and what it does to the data. I created another document term matrix that has less ingredients and is thus better for broad visualization. I then split that data by cuisine and manipulated the data to see what percent of the recipes for each cuisine contain a particular ingredient. I then added up all of those percents for each cuisine and got an estimate of how many ingredients are used in each cuisine's average recipes.

```
# remove some ingredients to have a more maneagable size for visualization
moreSparseDTM <- removeSparseTerms(dtm, 0.935)
smalldtm <- as.data.frame(as.matrix(moreSparseDTM))</pre>
smalldtm$cuisine <- as.factor(train$cuisine)</pre>
splitIngredients <- split(smalldtm, smalldtm$cuisine)</pre>
# since all of the cuisines have the same ingredients, deleting the last row
# of any cuisine will give you the ingredient names
ingredientNames <- names(splitIngredients$brazilian)</pre>
length(ingredientNames) <- (length(ingredientNames) - 1)</pre>
row.data <- c()
for (cuisine in splitIngredients) {
    # remove the cuisine column at the end
    woCuisine <- cuisine[, -(ncol(cuisine))]</pre>
    # add the column (ingredient) names back in
    names(woCuisine) <- ingredientNames</pre>
    # sum the column which will give you the number of times the ingredient was
    # used per cuisine
    ingPerCuisine <- colSums(woCuisine)</pre>
```

```
# dividing the columns by the number of recipes gives you an estimate of how
    # many ingredients are used in each cuisine's average recipes.
    ingPerCuisine <- ingPerCuisine/nrow(woCuisine)</pre>
    row.data <- c(row.data, ingPerCuisine)</pre>
}
ingPerCuisine.matrix <- rbind(row.data[1:90], row.data[91:180], row.data[181:270],</pre>
    row.data[271:360], row.data[361:450], row.data[451:540], row.data[541:630],
    row.data[631:720], row.data[721:810], row.data[811:900], row.data[901:990],
    row.data[991:1080], row.data[1081:1170], row.data[1171:1260], row.data[1261:1350],
    row.data[1351:1440], row.data[1441:1530], row.data[1531:1620], row.data[1621:1710],
    row.data[1711:1800])
rownames(ingPerCuisine.matrix) <- names(splitIngredients)</pre>
ingPerCuisine.matrix[1:3, 1:10]
##
                                                                   bell
                 allpurpos
                                  basil
                                             bean
                                                        beef
## brazilian
                0.03854390 0.004282655 0.1520343 0.06638116 0.1713062
                0.54228856\ 0.023631841\ 0.5808458\ 0.22388060\ 0.1169154
## british
## cajun_creole 0.03751617 0.291073739 0.3589909 0.34734799 0.6423027
##
                     black
                             boneless
                                             breast
                                                          broth
                                                                      brown
                0.28479657 0.03426124 0.0364025696 0.070663812 0.04496788
## brazilian
                0.06716418 0.06716418 0.0323383085 0.388059701 0.08084577
## british
## cajun creole 0.43014230 0.02199224 0.0006468305 0.009055627 0.20051746
ingredientsPerRecipe <- rowSums(ingPerCuisine.matrix)</pre>
par(las = 2)
par(mar = c(5, 8, 4, 2))
barplot(ingredientsPerRecipe, xlab = "Cuisines", cex.names = 0.5, main = "Average Ingredients Per Recip
```

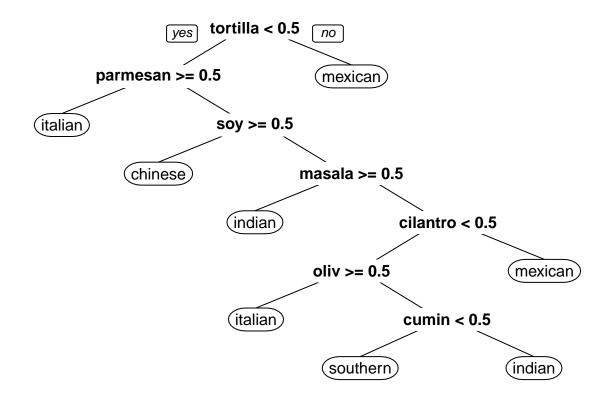
Average Ingredients Per Recipe



After that, I wanted to create a decision tree that would predict the cuisine of a recipe based on it's ingredients. To do this, I split up my data into a training and test set, and made a model with the training data. I then created a rpart decision tree model and ran it on my test set data. I then qualified my results with a confusion matrix.

```
####### Decision Tree ######
inTrain <- createDataPartition(y = ingredientsDTM$cuisine, p = 0.6, list = FALSE)
training <- ingredientsDTM[inTrain, ]
testing <- ingredientsDTM[-inTrain, ]

treemodel <- rpart(cuisine ~ ., data = training, method = "class")
prp(treemodel)</pre>
```



```
# Predict using the decision tree
prediction <- predict(treemodel, newdata = testing, type = "class")

# confusion matrix
CM <- confusionMatrix(prediction, testing$cuisine)
CM</pre>
## Confusion Matrix and Statistics
```

Confusion Matrix and Statistics ## ## Reference ## Prediction brazilian british cajun_creole chinese filipino french ## brazilian ## british ## cajun_creole ## chinese ## filipino ## french ## greek ## indian ## irish ## italian ## jamaican ## japanese ## korean ## mexican ## moroccan

##	russian		0	0		0		0	0		0
##	southern_us		99	279		412	2	05	163	7	723
##	spanish		0	0		0		0	0		0
##	thai		0	0		0		0	0		0
##	vietnamese		0	0		0		0	0		0
##	Reference										
##	Prediction	greek :	indian	irish	italian	jama	ican	japanes	e koı	rean	mexican
##	brazilian	0	0	0	0	_	0		0	0	0
##	british	0	0	0	0		0		0	0	0
##	cajun_creole	0	0	0	0		0		0	0	0
##	chinese	3	16	1	7		38	30	0	206	10
##	filipino	0	0	0	0		0		0	0	0
##	french	0	0	0	0		0		0	0	0
##	greek	0	0	0	0		0		0	0	0
##	indian	7	554	2	3		7	2	8	0	181
##	irish	0	0	0	0		0		0	0	0
##	italian	315	72	24	2202		20	1	4	3	220
##	jamaican	0	0	0	0		0		0	0	0
##	japanese	0	0	0	0		0		0	0	0
##	korean	0	0	0	0		0		0	0	0
##	mexican	4	239	5	25		16	1		10	1588
##	moroccan	0	0	0	0		0		0	0	0
##	russian	0	0	0	0		0		0	0	0 570
##	southern_us	141 0	320 0	234	898 0		129 0	21	0	113	576 0
##	spanish thai	0	0	0	0		0		0	0	0
##	vietnamese	0	0	0	0		0		0	0	0
##		Referenc	-	· ·	V		O		•	O	O
	Prediction			sian so	outhern_u	ıs sp	anish	thai v	ietna	amese	9
##					_						
	brazilian		0	0		0	0	0		()
##	brazilian british		0	0		0	0			(
								0)
##	british		0	0	1	0	0	0		())
## ##	british cajun_creole		0	0	1	0	0	0 0 206)) 88))
## ## ##	british cajun_creole chinese		0 0 1	0 0 2	1	0 0 4	0 0 2	0 0 206 0)) 88) 5)
## ## ## ##	british cajun_creole chinese filipino		0 0 1 0 0	0 0 2 0		0 0 14 0 0	0 0 2 0 0	0 0 206 0 0)) !8)) 5)
## ## ## ## ## ##	british cajun_creole chinese filipino french greek indian	3	0 0 1 0 0 0	0 0 2 0 0 0		0 0 14 0 0 0	0 0 2 0 0 0	0 0 206 0 0 0) 88 () () ()) 5)))
## ## ## ## ## ##	british cajun_creole chinese filipino french greek indian irish		0 0 1 0 0 0 0 0 32	0 0 2 0 0 0 1	1	0 0 14 0 0 0 0 8 0	0 0 2 0 0 0 2	0 0 206 0 0 0 11) 38 30 30 30 31 31 31 31 31 31 31 31 31 31 31 31 31) 5 0 0 0 1
## ## ## ## ## ##	british cajun_creole chinese filipino french greek indian irish italian		0 0 1 0 0 0 0 32 0	0 0 2 0 0 0 1 0 26	1	0 0 24 0 0 0 0 8 0	0 0 2 0 0 0 2 0 2 2	0 0 206 0 0 0 11 0) (88 (0 (0 (1 (1) 5 0 0 0 1 1
## ## ## ## ## ## ##	british cajun_creole chinese filipino french greek indian irish italian jamaican		0 0 1 0 0 0 0 32 0 27	0 0 2 0 0 0 1 0 26 0	1	0 0 4 0 0 0 0 0 8 0 0 7	0 0 2 0 0 0 2 0 2 2 7	0 0 206 0 0 0 11 0 14) 28 39 30 11 12 33 33) 5 5 0 0 0 1 1 0 3
## ## ## ## ## ## ##	british cajun_creole chinese filipino french greek indian irish italian jamaican japanese		0 0 1 0 0 0 0 32 0 27 0	0 0 2 0 0 0 1 0 26 0	1	0 0 24 0 0 0 0 8 0 0 7 0	0 0 2 0 0 0 2 0 227 0	0 0 206 0 0 0 11 0 14 0		() () () () () () ())) 5))) 1)) 3)
## ## ## ## ## ## ##	british cajun_creole chinese filipino french greek indian irish italian jamaican japanese korean	12	0 0 1 0 0 0 0 32 0 27 0 0	0 0 2 0 0 0 1 0 26 0 0	19	0 0 4 0 0 0 0 8 0 0 7 0 0	0 0 2 0 0 2 0 227 0 0	0 0 206 0 0 0 11 0 14 0) () () () () () () ()	0 0 5 0 0 1 0 3 0 0
## ## ## ## ## ## ## ##	british cajun_creole chinese filipino french greek indian irish italian jamaican japanese korean mexican	12	0 0 1 0 0 0 0 32 0 27 0 0 0	0 0 2 0 0 0 1 0 26 0 0	19	0 0 0 4 0 0 0 0 8 0 0 7 0 0 0	0 0 2 0 0 0 2 0 227 0 0 0	0 0 206 0 0 0 11 0 14 0 0		() () () () () () () () () () () ()	0 0 5 0 0 0 1 1 0 3 3 0 0 0
## ## ## ## ## ## ## ##	british cajun_creole chinese filipino french greek indian irish italian jamaican japanese korean mexican moroccan	12	0 0 1 0 0 0 0 32 0 27 0 0 0 0	0 0 2 0 0 0 1 0 26 0 0 0	19	0 0 0 4 0 0 0 0 8 0 0 7 0 0 0 0 0 0 0 0 0 0 0 0	0 0 2 0 0 0 2 2 0 0 227 0 0 0 40 0	0 0 206 0 0 0 11 0 14 0 0 0		() 85 () () () () () () () ()	0 0 5 0 0 0 1 1 0 3 0 0 0 0 0 1 0 0 0 0 0 0 0
## ## ## ## ## ## ## ##	british cajun_creole chinese filipino french greek indian irish italian jamaican japanese korean mexican moroccan russian	1:	0 0 1 0 0 0 0 32 0 27 0 0 0 0	0 0 2 0 0 0 1 0 26 0 0 0	19	0 0 0 4 0 0 0 0 8 0 0 7 0 0 0 0 0 0 0 0 0 0 0 0	0 0 2 0 0 2 0 227 0 0 0 40 0	0 0 206 0 0 0 11 0 14 0 0 0		() 85 () () () () () () () ()	0 0 5 0 0 0 1 0 0 3 0 0 0 0 0 1 0 0 0 0 0 0 0
## ## ## ## ## ## ## ## ##	british cajun_creole chinese filipino french greek indian irish italian jamaican japanese korean mexican moroccan russian southern_us	1:	0 0 1 0 0 0 0 32 0 27 0 0 0 0 14 0 0	0 0 2 0 0 0 1 0 26 0 0 0 26 0	19	0 0 0 24 0 0 0 0 8 0 0 7 0 0 0 0 0 0 0 0 0 0 0 0	0 0 2 0 0 227 0 0 227 0 40 0	0 0 206 0 0 0 11 0 14 0 0 0 197 0		() 85 () () () () () () () () () ()	0 0 5 0 0 0 1 0 0 0 0 0 0 1 0 0 0 0 0 0
## ## ## ## ## ## ## ## ## ##	british cajun_creole chinese filipino french greek indian irish italian jamaican japanese korean mexican moroccan russian southern_us spanish	1:	0 0 1 0 0 0 0 32 0 27 0 0 0 0 14 0 0	0 0 2 0 0 0 1 0 26 0 0 0 2 0 0	19	0 0 0 14 0 0 0 0 8 0 0 7 0 0 0 0 0 0 0 0 0 0 0 0	0 0 2 0 0 0 227 0 0 40 0 0 124 0	0 0 206 0 0 0 11 0 14 0 0 0 197 0 187		() 85 () () () () () () () () () () ()	0 0 5 0 0 0 1 0 0 3 3 0 0 0 0 1 0 0 0 0 0 0 0
## ## ## ## ## ## ## ## ## ##	british cajun_creole chinese filipino french greek indian irish italian jamaican japanese korean mexican moroccan russian southern_us spanish thai	1:	0 0 1 0 0 0 0 32 0 27 0 0 0 0 14 0 0	0 0 2 0 0 0 1 0 26 0 0 0 2 0 0 0 1 0 0 0 1 0 0 0 0 0 0 0 0	19	0 0 0 14 0 0 0 0 8 0 0 0 0 0 0 0 0 0 0 0 0 0 0	0 0 2 0 0 0 2 2 7 0 0 40 0 0 124 0	0 0 206 0 0 0 11 0 14 0 0 0 197 0 0 187		() () () () () () () () () () () ()	0 0 5 0 0 0 0 1 0 0 0 0 0 1 0 0 0 0 0 0
## ## ## ## ## ## ## ## ## ##	british cajun_creole chinese filipino french greek indian irish italian jamaican japanese korean mexican moroccan russian southern_us spanish	1:	0 0 1 0 0 0 0 32 0 27 0 0 0 0 14 0 0	0 0 2 0 0 0 1 0 26 0 0 0 2 0 0	19	0 0 0 14 0 0 0 0 8 0 0 7 0 0 0 0 0 0 0 0 0 0 0 0	0 0 2 0 0 0 227 0 0 40 0 0 124 0	0 0 206 0 0 0 11 0 14 0 0 0 197 0 0 187		() 85 () () () () () () () () () () ()	0 0 5 0 0 0 0 1 0 0 0 0 0 1 0 0 0 0 0 0
## ## ## ## ## ## ## ## ## ## ##	british cajun_creole chinese filipino french greek indian irish italian jamaican japanese korean mexican moroccan russian southern_us spanish thai	1:	0 0 1 0 0 0 0 32 0 27 0 0 0 0 14 0 0	0 0 2 0 0 0 1 0 26 0 0 0 2 0 0 0 1 0 0 0 1 0 0 0 0 0 0 0 0	19	0 0 0 14 0 0 0 0 8 0 0 0 0 0 0 0 0 0 0 0 0 0 0	0 0 2 0 0 0 2 2 7 0 0 40 0 0 124 0	0 0 206 0 0 0 11 0 14 0 0 0 197 0 0 187		() () () () () () () () () () () ()	0 0 5 0 0 0 0 1 0 0 0 0 0 1 0 0 0 0 0 0
## ## ## ## ## ## ## ## ## ## ##	british cajun_creole chinese filipino french greek indian irish italian jamaican japanese korean mexican moroccan russian southern_us spanish thai vietnamese	1:	0 0 1 0 0 0 0 32 0 27 0 0 0 0 14 0 0	0 0 2 0 0 0 1 0 26 0 0 0 2 0 0 0 1 0 0 0 1 0 0 0 0 0 0 0 0	19	0 0 0 14 0 0 0 0 8 0 0 0 0 0 0 0 0 0 0 0 0 0 0	0 0 2 0 0 0 2 2 7 0 0 40 0 0 124 0	0 0 206 0 0 0 11 0 14 0 0 0 197 0 0 187		() () () () () () () () () () () ()	0 0 5 0 0 0 0 1 0 0 0 0 0 1 0 0 0 0 0 0
## ## ## ## ## ## ## ## ## ## ##	british cajun_creole chinese filipino french greek indian irish italian jamaican japanese korean mexican moroccan russian southern_us spanish thai vietnamese	1:	0 0 1 0 0 0 0 32 0 27 0 0 0 14 0 0 54 0	0 0 2 0 0 0 1 0 26 0 0 0 0 26 0 0 0 0	19	0 0 0 14 0 0 0 0 8 0 0 0 0 0 0 0 0 0 0 0 0 0 0	0 0 2 0 0 0 2 2 7 0 0 40 0 0 124 0	0 0 206 0 0 0 11 0 14 0 0 0 197 0 0 187		() () () () () () () () () () () ()	0 0 5 0 0 0 0 1 0 0 0 0 0 1 0 0 0 0 0 0
## ## ## ## ## ## ## ## ## ## ## ## ##	british cajun_creole chinese filipino french greek indian irish italian jamaican japanese korean mexican moroccan russian southern_us spanish thai vietnamese	1: 1: ! tics	0 0 1 0 0 0 0 32 0 27 0 0 0 14 0 0 0 54 0	0 0 2 0 0 0 1 0 26 0 0 0 2 0 0 0 1 1 0 0 0 0 0 0 0 0 0 0 0	19	0 0 0 14 0 0 0 0 8 0 0 0 0 0 0 0 0 0 0 0 0 0 0	0 0 2 0 0 0 2 2 7 0 0 40 0 0 124 0	0 0 206 0 0 0 11 0 14 0 0 0 197 0 0 187		() () () () () () () () () () () ()	0 0 5 0 0 0 0 1 0 0 0 0 0 1 0 0 0 0 0 0

```
##
       No Information Rate: 0.1971
##
       P-Value [Acc > NIR] : < 2.2e-16
##
##
                      Kappa: 0.3285
##
    Mcnemar's Test P-Value : NA
##
## Statistics by Class:
##
##
                         Class: brazilian Class: british Class: cajun_creole
                                                  0.00000
                                                                       0.00000
## Sensitivity
                                   0.0000
## Specificity
                                   1.0000
                                                  1.00000
                                                                        1.00000
## Pos Pred Value
                                       NaN
                                                      NaN
                                                                            NaN
## Neg Pred Value
                                   0.9883
                                                  0.97982
                                                                        0.96114
                                   0.0117
## Prevalence
                                                  0.02018
                                                                        0.03886
## Detection Rate
                                   0.0000
                                                  0.00000
                                                                        0.00000
## Detection Prevalence
                                   0.0000
                                                  0.00000
                                                                        0.00000
                                                  0.50000
                                                                        0.50000
## Balanced Accuracy
                                   0.5000
##
                         Class: chinese Class: filipino Class: french
                                0.76988
                                                 0.00000
                                                                0.00000
## Sensitivity
## Specificity
                                0.93104
                                                 1.00000
                                                                1.00000
## Pos Pred Value
                                0.44583
                                                     NaN
                                                                    NaN
## Neg Pred Value
                                0.98250
                                                 0.98101
                                                                0.93347
## Prevalence
                                                                0.06653
                                0.06722
                                                 0.01899
## Detection Rate
                                0.05175
                                                 0.00000
                                                                0.00000
                                0.11608
## Detection Prevalence
                                                 0.00000
                                                                0.00000
## Balanced Accuracy
                                0.85046
                                                 0.50000
                                                                0.50000
##
                         Class: greek Class: indian Class: irish
                              0.00000
                                             0.46128
                                                           0.00000
## Sensitivity
                                                           1.00000
## Specificity
                              1.00000
                                             0.97762
## Pos Pred Value
                                             0.62741
                                                               NaN
                                  NaN
## Neg Pred Value
                              0.97045
                                             0.95692
                                                           0.98327
## Prevalence
                              0.02955
                                             0.07552
                                                           0.01673
## Detection Rate
                              0.00000
                                             0.03484
                                                           0.00000
## Detection Prevalence
                                             0.05552
                                                           0.00000
                              0.00000
## Balanced Accuracy
                              0.50000
                                             0.71945
                                                           0.50000
                         Class: italian Class: jamaican Class: japanese
## Sensitivity
                                 0.7024
                                                 0.00000
                                                                  0.00000
## Specificity
                                 0.8543
                                                 1.00000
                                                                  1.00000
## Pos Pred Value
                                 0.5421
                                                     NaN
                                                                      NaN
## Neg Pred Value
                                                 0.98679
                                                                  0.96422
                                 0.9212
## Prevalence
                                                                  0.03578
                                 0.1971
                                                 0.01321
## Detection Rate
                                                 0.00000
                                                                  0.00000
                                 0.1385
## Detection Prevalence
                                 0.2554
                                                 0.00000
                                                                  0.00000
                                                 0.50000
## Balanced Accuracy
                                 0.7784
                                                                  0.50000
                         Class: korean Class: mexican Class: moroccan
## Sensitivity
                               0.00000
                                               0.61670
                                                                0.00000
## Specificity
                               1.00000
                                               0.93487
                                                                1.00000
## Pos Pred Value
                                   NaN
                                               0.64658
                                                                    NaN
                               0.97912
## Neg Pred Value
                                               0.92660
                                                                0.97937
## Prevalence
                               0.02088
                                               0.16192
                                                                0.02063
## Detection Rate
                               0.00000
                                                                0.00000
                                               0.09986
## Detection Prevalence
                               0.00000
                                               0.15444
                                                                0.00000
## Balanced Accuracy
                               0.50000
                                               0.77579
                                                                0.50000
##
                         Class: russian Class: southern_us Class: spanish
```

##	Sensitivity	0.00000	0.85417	0.00000
##	Specificity	1.00000	0.63457	1.00000
##	Pos Pred Value	NaN	0.22175	NaN
##	Neg Pred Value	0.98774	0.97275	0.97516
##	Prevalence	0.01226	0.10866	0.02484
##	Detection Rate	0.00000	0.09281	0.00000
##	Detection Prevalence	0.00000	0.41854	0.00000
##	Balanced Accuracy	0.50000	0.74437	0.50000
##		Class: thai Class:	vietnamese	
##	Sensitivity	0.00000	0.0000	
##	Specificity	1.00000	1.00000	
##	Pos Pred Value	NaN	NaN	
##	Neg Pred Value	0.96133	0.97925	
##	Prevalence	0.03867	0.02075	
##	Detection Rate	0.00000	0.0000	
##	Detection Prevalence	0.00000	0.0000	
##	Balanced Accuracy	0.50000	0.50000	

As you can see, my accuracy rate is fairly low at 40% overall accuracy. However, my model preforms 8 times better than pure chance and a little over twice as well as just predicting every recipe as Italian.